Eksploatacja i Niezawodnosc – Maintenance and Reliability
Volume 23 (2021), Issue 2
journal homepage: http://www.ein.org.pl

Article citation info:
Jasiulewicz–Kaczmarek M, Antosz K. Żywica P, Mazurkiewicz D, Sun B, Ren Y. Framework of machine criticality assessment with criteria interactions. Eksploatacja i Niezawodnosc – Maintenance and Reliability 2021; 23 (2): 207–220, http://doi.org/10.17531/ein.2021.2.1.

Framework of machine criticality assessment with criteria interactions

Indexed by: Web of Science Group

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Highlights

- A review of machines criticality assessment criteria was presented.
- A novel model of a machine criticality assessment is proposed.
- The model combines the importance of the machine criticality assessment criteria with interactions between them.
- The machine criticality assessment model for the aviation industry is presented.

Abstract

Criticality is considered as a fundamental category of production planning, maintenance process planning and management. The criticality assessment of machines and devices can be a structured set of activities allowing to identify failures which have the greatest potential impact on the company's business goals. It can be also used to define maintenance strategies, investment strategies and development plans, assisting the company in prioritizing their allocations of financial resources to those machines and devices that are critical in accordance with the predefined business criteria. In a criticality assessment process many different and interacting criteria have to be taken into consideration, despite the fact that there is a high level of uncertainty related to various parameters. In addition, not all assessment criteria are equally important. Therefore, it is necessary to determine the weight of each criterion taking into account different requirements of machine criticality process stakeholders. That is why a novel model of a machine criticality assessment is proposed in this paper. The model extends the existing methods of assessing machines criticality, taking into account not only the importance of machine criticality assessment criteria, but also possible interactions between them.

Keywords

machine criticality assessment, assessment criteria, assessment methods, interactions.

1. Introduction

The recent rapid development of production systems related to automatization and digitalization has required a new approach to defining the function and role of a technical object in a production processes. Due to the client's requirements for a product, the technologies used for their realization and the impact of failures on people and natural environment, the companies not only must plan maintenance activities, but also have to define the priorities for implementations of these activities taking into account the role they play in business goals [13, 41, 75]. Therefore, an important issue for any company is a machine criticality assessment. Referring to [1, 4, 70] criticality is a fundamental category of the production and maintenance process planning and management. A machine and device criticality assessment is a structured set of activities that allows to identify machines and devices which failures have the greatest potential impact on the company's business goals. It can be used to define maintenance strategies, investment strategies and development plans, assisting the company in prioritizing the allocation of financial resources to those machines and devices that are critical in accordance with the predefined business criteria [27, 37, 47, 60, 89]. Moreover, according to Roy [70], prioritizing of maintenance activities eliminates their instability and variability in activities, thereby increasing resource efficiency and reducing maintenance costs.

Although the literature review describes many methods for assessing the machine criticality and decision making systems in this area, itis still not a simple task [6, 13, 40, 48]. First of all, in a machine criticality assessment process many different and interacting criteria have to be taken into consideration [21]. Secondly, due to the quality and method of data acquisition there is a high level of uncertainty related to various parameters such as: time between failures, time to repair and the quantity of spare parts needed for a repair [46]. Thirdly, not all assessment criteria are equally important. Therefore, it is neces-

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sary to determine the weight of each criterion taking into account different requirements of machine criticality process stakeholders [75]. Considering the above issues, a novel model of a machine criticality assessment is proposed in this paper. The proposed model extends the methods of assessing the machine criticality described in the literature and used in practice taking into account not only the importance of machine criticality assessment criteria, but also the interactions between them.

This paper is organized as follows: in Section 2 the literature review according the criteria and methods used for a machine criticality assessment is presented. Then, in Section 3 a novel framework of a machine criticality assessment is developed. Moreover, in this section the study results of the importance for the criticality assessment in different industries are presented. In Section 4 a machine criticality assessment model for the aviation industry is presented. Finally, the conclusions and direction of the future research are presented.

2. Problem statement of a machine criticality assessment

2.1. Criticality criteria

As mentioned in work [80], criticality is a measure of importance defined on the basis of the analyzed factors. Moreover, criticality is used as a comparative measure to assess the consequences of actions taken and it can be used as a measure to highlight the differences between individual machines and action scenarios (action strategies). The criteria adopted for the evaluation may affect the final criticality often differ from one organization to another. They are often dependent on the type of assets (resources) as well as adopted rules in the organization. In the literature many criteria for assessing the criticality of machines are defined. Because the classification of the criteria for assessing the criticality of machines proposed in the literature is not unambiguous and may cause problems related to their interpretation two – level- hierarchical classification for the machine criticality assessment criteria was proposed in Table 1.

Moreover, in the literature in different areas, other criteria of machine criticality assessment are proposed. In the area of manufacturing systems, the following factors are indicated: redundancy, work load [4], production integrity [18, 50, 63, 86], machine importance for a process [5], breakdown time and stability of the machine [75], sensitivity of operation [36], bottleneck and impact on throughput [44], applicability of CBM [63] and reliability [54, 63].

Furthermore, in the medical assessment, the following criteria are used: risk, user competence and standards [71], performance assurance [14, 71], support availability, clinical acceptability [14], function [14, 80], recalls and hazard alerts and maintenance requirements [80].

In the oil refinery assets the following criteria are proposed: failure detection and failure severity [33]. What's more, the customer's inconvenience criterion [74] and effect of power generation in thermal power plants equipment assessment [34] as well as the impact of business (shutdown duration) in chemical plants equipment assessment [65] are proposed.

2.2. Criticality method assessment used and criticality levels

There are many different methods presented in the literature for assessing the criticality of machines. These methods use a variety of evaluation criteria and are used in different industries. The most

Table 1. Criteria for assessing the criticality of machines – literature survey

No	Main criteria	Sub - criteria	References
1.	Safety	Degree of influence on working conditions. Machine failure costs due to health, safety and environment.	[5, 18, 24, 26, 34, 38, 50, 53, 54, 63, 64, 65, 66, 67, 75, 86]
2.	Environment	In case of failure, the degree of risk for the environment. Working environment.	[26, 28, 34, 53, 54, 64, 65, 74, 86]
3.	Maintainability	MTTR (Mean Time To Repair). OEE (Overall Equipment Effectiveness). Failure detection. Failure frequency. Failure severity. Downtime length.	[2, 5, 16, 19, 20, 31, 33, 41, 43, 53, 63, 6, 73, 75, 79, 92]
4.	Quality	The degree of influence of a machine on the implementation of other operations in case of a failure. Number of nonconformities due to the machine failure during the year. The degree of influence of a technical object on the quality of the final product. Costs of non-conforming products as a result of a failure.	[4, 18, 19, 20, 26, 31, 50, 54, 66, 67, 68, 90]
5.	Age	Age of machine.	[4, 14, 68, 80]
6.	Cost	Costs incurred by production for machine downtime (breakdown). Costs of non-conforming products as a result of failure. Failure elimination costs (excluding OHS and environmental costs). Machine failure costs due to health, safety and environment.	[4, 5, 6, 14, 19, 20, 26, 31, 33, 53, 65, 68, 72, 74]
7.	Risk	Mission criticality. Operating conditions and equipment accidents.	[19, 20, 28, 31, 80]
8	Availability	Average downtime of a technical facility due to failures and repairs. Availability of the required personnel. MTBF (Mean Time Between Failures). Machine replacement in case of failure (Machine changeability). Work load.	[2, 31, 43, 53, 63, 66, 67, 76]
9.	Spare parts	Spare parts availability.	[36, 63]

commonly used method is the AHP (Analytical Hierarchy Process) method. This method is used to select the best alternative and analyze possible alternatives [17, 76, 84]. In the work [5] the authors indicate that thanks to the great alternatives it can be used to arrange a large number of machines. In order to create the ranking, it is possible to integrate both qualitative and quantitative criteria, as well as their integration [14, 46, 69]. The AHP method has been successfully applied to the classification of equipment in the thermal power plant [34, 74], for the prioritization in the medical industry [80] and machinery classification in the plastics processing industry [1]. Moreover, the authors in [76] noted that it can be integrated with other methodologies, such as the Delphi method. This method relies heavily on experts. Such integration into the classification of equipment in an oil refinery is presented in [33]. In [85] it was noted that the calculation of the coefficients of coherence makes this method more reliable compared to the additive weighting method presented in [31, 75].

Additionally, in order to evaluate the criticality of machines, the rules of interconnection with the fuzzy logic and fuzzy grouping are used. The result of this assessment is the identification of different categories of machines. Rules are an appropriate method to evaluate a large number of machines for which common strategies and operating procedures are defined [41, 54]. The combination of rules with the fuzzy logic is presented in [36]. Furthermore, [28] presents a fuzzy cluster analysis structure divided into four sub-hierarchy models. Fuzzy grouping is also presented in the literature as a possible method for assessing the importance or criticality of equipment. Guo et al. [26] found that fuzzy assessments can deal with imprecise information better, which can be beneficial for companies. However, its effective application depends on the function of membership and a set of weighting factors. The fuzzy logic application has some advantages. However, it is a complex methodology and difficult to advance as it requires some simulations before use [85].

Moreover, in the literature, the FMEA method (Failure Mode And Effects Analysis) is used to assess the criticality of machines. It allows the identification of the factors that were taken into account for the criticality assessment. Most often this method is used to assess the types of failures, with particular emphasis on the likelihood of failures and their consequences, taking into account such factors as: redundancy, use, quality, age of machine and costs [4, 68]. Another variant of the FMEA – FMCEA (Failure Mode, Effects, And Criticality Analysis) method takes into account additional factors such as environmental aspects when assessing criticality [12]. Based on the value of RPN (Risk Priority Number) index and risk matrix the machine criticality and the maintenance strategy are determined.

The applied criticality method allows to determine the machine criticality level (machine category). The authors in the works [8, 29, 57, 82] classified machines into three groups on the basis of the ABC (Activity Based Classification) analysis method. The main goal of this method is based on Pareto's principle, which classifies the top 15–20% goods occupied 65–80% value of the whole system into A group, the following 30–40% goods occupied 15–20% value of the whole system into B group, and the other 40–55% goods occupied 5–15% value of the whole system into C group [29]. Additionally, a scoring system is used to assess the criticality [68, 75]. The authors of the mentioned works used ABC or ABCD classification levels. ABC – type classifies machines into three groups: category A – machines which need special control, category B – machines which need less control and category C – machines which do not need any special control. The ABCD - type classification defines four categories of machines as: category A – particularly important (bottleneck), category B – important, category C – relatively important, category D – not used.

In addition to the ABC classification, there is another method of assessing the criticality of machines, that is the GUT (Gravity, Urgency and Tendency) matrix [15].

2.3. Research challenges

The analysis of the literature showed that many criteria are proposed for assessing the criticality of machines. The same criteria are often defined differently, e.g. breakdown /failure. Moreover, sometimes it is difficult to understand the meaning of the criterion unequivocally on the basis of the description provided by the author. The criteria analysis presented in Table 1 allowed to systematize them. Nevertheless, there are no unequivocal studies indicating the real usefulness and importance of the specific criteria for different industries.

In addition, various methods are available for assessing the criticality. These methods take into account various criteria proposed (as discussed above). However, these criteria are often analyzed independently, or their dependence is analyzed to a little extent. In the literature, the method that takes into account the interactions between the individual evaluation criteria used to assess the criticality of machines is not described. From the point of view of the machine criticality assessment, most of the proposed criteria aggregation methods have some drawbacks. Namely, they do not reflect the interaction between the criteria. In the real manufacturing environment machine criticality criteria are usually not independent (there are some interactions among the criteria, positive or negative effects between them) Thus, an appropriate function must be used to aggregate multiple information sources and to handle an interactive relationship. An example of such an environment is a noisy environment where complex criterion relationships between worker and machine can be identified [61]. Since ignoring the interaction between the assessment criteria may lead to distortions of its outcome and, consequently, ineffective and inefficient decisions, commonly used aggregation and ranking methods such as AHP, SAW and WSAW do not apply in this problem.

That is why, in this paper, a new method of machine criticality assessment is proposed.

As part of the work, the following research questions were taken into consideration:

1. Is there a difference in the perception of the criteria importance of the machine criticality assessment in various industries?
2. Which method is able to model the importance of machine criticality assessment criteria and the interaction between them?
3. How important are the particular machine criticality assessment criteria and the interactions between them in the case study industry?

3. The framework of machine criticality assessment

3.1. Development of the methodology

Machine criticality is a complex concept and depends on many factors. "Intuition" is usually not sufficient to make an objective decision about which machine is important and which is not. It is necessary to build a structured method to support decision makers in the machine criticality assessment process. A general scheme of the machine criticality assessment method used in this paper includes three main stages: (1) Selection of criteria, (2) Criteria assessment, and (3) Selection of the appropriate aggregation function (Figure 1).

Based on the final Machine Criticality Index (MCI), it is possible to define the prioritization of maintenance actions in order to ensure that the production system works as close to its nominal capacity as possible.

3.2. Identification of criticality assessment criteria

The main standard for evaluating the machine criticality is the criteria. Based on the analysis of the literature (chapter 2.1), 24 criteria most frequently matched and used to assess the criticality of machines were selected: C1 - Operators' competences; C2 - Machine replacement in case of failure; C3 - Degree of influence on other tasks in case of a failure; C4 - Costs incurred by production for machine downtime (breakdown); C5 - Number of nonconformities due to a machine failure during the year; C6 – Degree of machine influence on the final

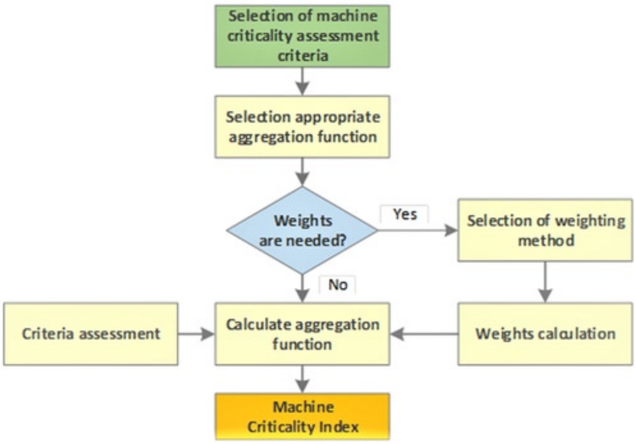

Fig. 1. A generic process for the machine criticality assessment

product quality; C7 - Costs of non-conforming products as the result of a failure; C8 - Frequency of failures per year; C9 - Average downtime of a technical facility due to failures and repairs; C10 – Spare parts availability; C11 - Failure elimination costs (excluding OHS and environmental costs); C12 - In case of a failure, the degree of influence on working environment; C13 - In case of a failure, the degree of risk to environment; C14 - Machine failure costs due to health, safety and environment; C15 - Age of the machine; C16 - OEE; C17 - MTBF; C18 - MTTR; C19 - Failure severity; C20 - Failure detection; C21 - Customer's inconvenience; C22 - Mission criticality; C23 - Operating condition; C24 - Work load.

In the next step, these criteria were assessed by company experts in order to identify the most important criteria from the industry point of view. The research on the perception of the importance of the machine criteria criticality assessment was carried out at the turn of 2019 in 2020 in small, medium-sized and large production companies of various industries selected for the research purposely. A group of 66 production companies participated in the study, of which 22.39% were enterprises from the automotive industry, 29.85% from the food industry, 31.34% from the aviation industry and 16.42% from other industries, e.g. medical, furniture, railway, printing house, etc. The biggest group of them was the large enterprises 57.58%, and smallest group was small sized companies (6.06%) (Figure 2).

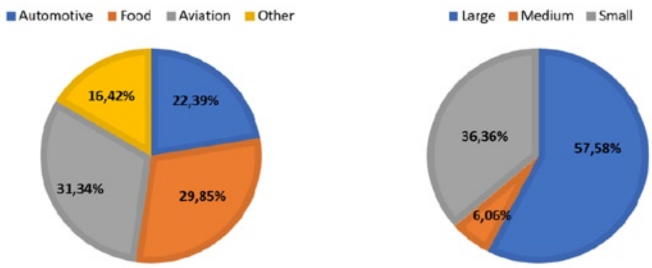

Fig. 2. Structure of the enterprises participating in the survey

The survey was conducted with experts from these enterprises. The experts were asked to determine the degree of importance of the 24 criteria on a scale from 1 to 5, where 1 meant – not important, while 5 very important. The data set obtained from the enterprises was subjected to a statistical assessment (an average assessment value - $\overline{X}$, a standard deviation – S, $\sum$ - total importance obtained by the criterion in a given industry) (Table 2).

Analyzing the results presented in Table 1 there are visible differences not only in the assessment of the importance of the criteria in individual industries, but also in each individual criterion in a given industry. In case of the automotive industry, the highest compliance in the assessment of the criterion by enterprises was identified for the C5 criterion - the value of a standard deviation is s = 0.408. The lowest compliance was noted for the C16 criterion (s = 1.188). In the food and aviation industries, the highest compliance in the assessment of the importance was achieved by the C6 criterion, with the following values of a standard deviation - food s = 0.413, aviation s = 0.359. On the other hand, the lowest compliance was achieved by the C17 criterion in the food industry (s = 1.223), and the C24 criterion in the aviation industry (s = 0.949). Additionally, it should be noted that in case of the aviation industry, the values of the standard deviation for the assessed criteria were the lowest, what proves high consistency in assessing the importance of criteria in individual companies in this industry. In case of enterprises identified as "other", the highest compliance in the assessment of the criterion by the enterprises was identified for the C8 criterion - the standard deviation value is s = 0.601, and the lowest, the same as in the automotive industry, for C16 (s = 1.481). An average value of the importance obtained by the analyzed criteria for individual industries is presented in Figure 3.

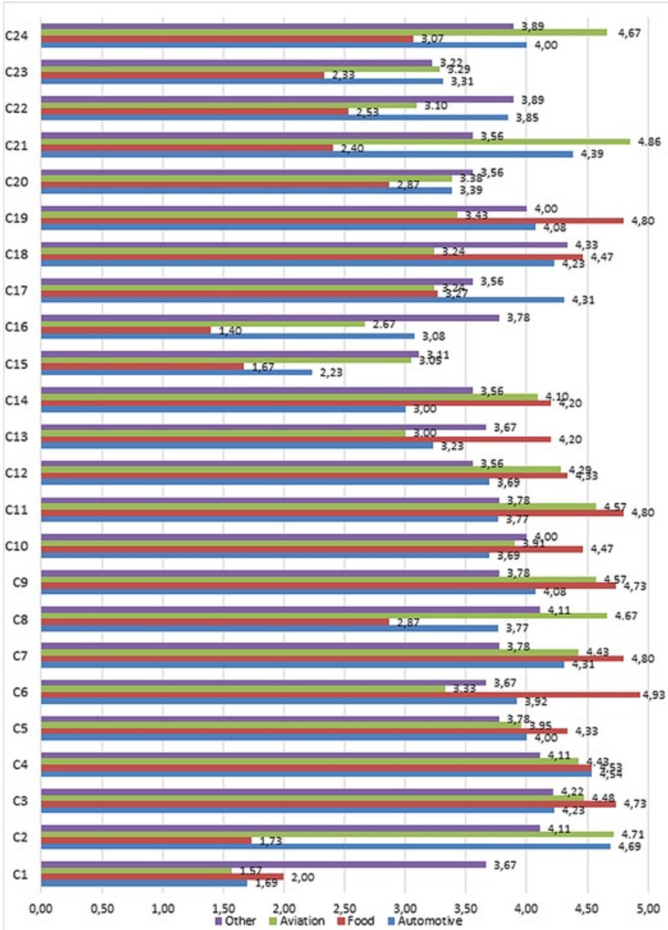

Fig. 3. An average assessment value of importance ($\overline{X}$) obtained by the analyzed criteria for individual industries

The analysis of the above results (Figure 3) made it possible to identify common assessment criteria for individual industries. When identifying the common criterion, similar or insignificant differences (± 0.5) in the obtained average assessment value ($\overline{X}$) for a particular criterion were taken into account. The criteria common for all industries are: C3, C4 and C5. However, the C1 and C7 criterion is common for the automotive, aviation and food industries. Criteria C2, C20, C22 and C23 are common for the aviation, automotive industries and the enterprises defined as "other". The C6 and C10 criterion obtained the highest value (4.93 and 4.47) for the food industry, but this criterion is common for aviation, automotive industries and the enterprises defined as "other". On the other hand, the C8, C15 and C16 criterion is common for the aviation industry and the enterprises defined as "other". Moreover, the C9 criterion obtained similar $\overline{X}$ values for

Table 2. Perception of machine criticality factors importance

Criteria	Automotive			Food			Aviation			Other		
	∑	$\bar{X}$	s	∑	$\bar{X}$	s	∑	$\bar{X}$	s	∑	$\bar{X}$	s
C1	22	1.692	0.480	30	2.000	0.655	33	1.571	0.676	33	3.667	1.414
C2	61	4.692	0.480	26	1.733	0.884	99	4.714	0.561	37	4.111	1.364
C3	55	4.231	0.725	71	4.733	0.458	94	4.476	0.814	38	4.222	0.972
C4	59	4.538	0.519	68	4.533	0.743	93	4.429	0.507	37	4.111	0.782
C5	52	4.000	0.408	65	4.333	0.900	83	3.952	0.669	34	3.778	0.833
C6	51	3.923	0.494	74	4.933	0.413	102	3.333	0.359	33	3.667	1.225
C7	56	4.308	0.630	72	4.800	0.414	93	4.429	0.598	34	3.778	1.394
C8	49	3.769	0.439	43	2.867	1.060	98	4.667	0.483	37	4.111	0.601
C9	53	4.077	0.760	71	4.733	0.458	96	4.571	0.507	34	3.778	0.667
C10	48	3.692	0.751	67	4.467	0.834	82	3.905	0.436	36	4.000	1.323
C11	49	3.769	0.439	72	4.800	0.414	96	4.571	0.507	34	3.778	0.833
C12	48	3.692	1.032	65	4.333	0.976	90	4.286	0.644	32	3.556	1.130
C13	42	3.231	1.013	63	4.200	0.941	98	3.000	0.483	33	3.667	1.118
C14	39	3.000	0.816	63	4.200	0.941	86	4.095	0.539	32	3.556	1.333
C15	29	2.231	0.599	25	1.667	0.488	64	3.048	0.590	28	3.111	0.782
C16	40	3.077	1.188	21	1.400	0.507	56	2.667	0.913	34	3.778	1.481
C17	56	4.308	1.109	49	3.267	1.223	68	3.238	0.539	32	3.556	1.130
C18	55	4.231	1.092	67	4.467	0.915	68	3.238	0.436	39	4.333	1.000
C19	53	4.077	0.641	72	4.800	0.414	72	3.429	0.598	36	4.000	1.000
C20	44	3.385	0.768	43	2.867	0.990	71	3.381	0.865	32	3.556	1.236
C21	57	4.385	0.650	36	2.400	0.507	70	4.857	0.577	32	3.556	0.882
C22	50	3.846	0.376	38	2.533	0.834	65	3.095	0.700	35	3.889	1.054
C23	43	3.308	0.630	35	2.333	0.617	69	3.286	0.463	29	3.222	0.833
C24	52	4.000	0.577	46	3.067	0.594	63	4.667	0.949	35	3.889	1.054
Legend:	(green)	the lowest value of a standard deviation (s) for every industry										
	(red)	the highest value of a standard deviation (s) for every industry										

the automotive industry and the enterprises defined as "other", with the values of 3.78 and 4.06, respectively. Moreover, it should be noted that this criterion obtained also similar values for the food and aviation industries, 4.73 and 4.57, respectively. Additionally, the criteria C11, C12 and C14 obtained the highest values for the food and aviation industries. The C21 and C24 criteria for the aviation industry achieved the highest values, respectively 4.86 and 4.67. On the other hand, the C13 criterion with the obtained average value of 4.20 and C19 with the average value 4.80 dominated in the food industry. This criterion obtained similar values for the aviation (3.00) and automotive (3.23) industries. The C17 criterion dominated in the automotive industry (with the average value of 4.31), but this criterion is common for the aviation, food industries and the enterprises defined as "other".

In Figure 4, the total importance obtained by the analyzed criteria for individual industries is presented. The presented results show which of the individual criteria obtained the highest total value for individual industries. In the aviation and automotive industries, the lowest value was obtained by the C1 criterion (value 33, 22). However, in the aviation industry, the highest value was obtained by the C6 criterion, which was also dominant in the food industry. The most important criterion in the automotive industry was the C2 criterion. A completely different situation can be noticed in the enterprises defined as "other". In this case, the C23 criterion had the lowest value and the C18 criterion the highest. What is more, it should be noted that the criteria from C2 to C14 in the aviation industry obtained the highest values among the surveyed criteria. On one hand, it is justified by the fact that most companies in this industry participated in the research. On the other hand, it turned out that these criteria are the most important from the point of view of machine criticality in this industry.

The criteria from C2 to C14 in the aviation industry were selected for a further analysis (model building). Additionally, the factors determining the choice of these criteria were: the largest number of companies in the aviation industry in the conducted research as well as the fact that in case of this industry, the values of the standard deviation (s) for the assessed criteria were the lowest, what proves a high consistency in assessing the importance of criteria in individual companies (conformity of the assessment).

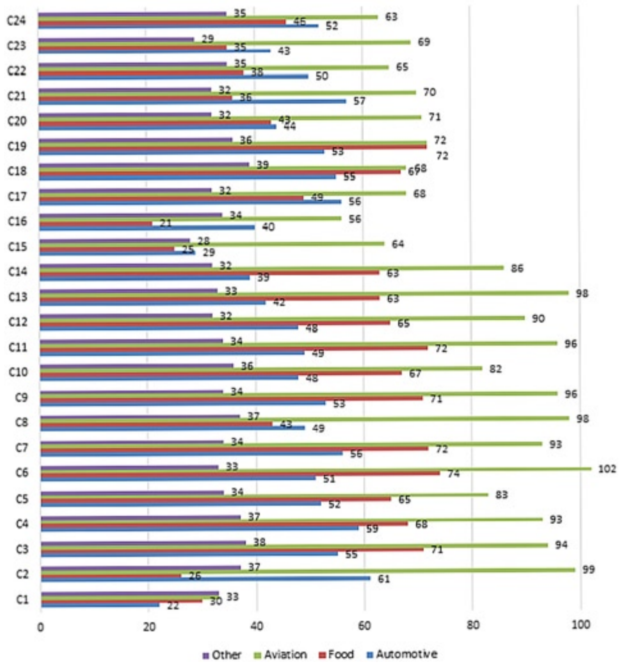

Fig. 4. The total importance obtained by the analyzed criteria for individual industries

After identifying the criteria that will be further analyzed, we can proceed to the next step, i.e. building a function that aggregates individual criteria values into one synthetic result.

3.3. Development of an aggregation function

3.3.1. Assumptions

The purpose of aggregation functions is to combine multiple numerical inputs into a single numerical value, which in some sense represents all the inputs. According to [3] many aggregation functions present some drawbacks, mainly from their natural assumption that input criteria are independent of each other (arithmetic mean, weighted mean, median, mode etc.) and none is capable to find an interaction between criteria [51]. However, this fact does not limit their usability in many complex areas of application [62, 87].

Because the criteria of the machine criticality assessment are usually not independent (there are some interactions among criteria, positive or negative effects among them), an appropriate function must be used to aggregate multiple information sources and to handle an interactive relationship.Based on the literature review [11, 22, 45], in order to solve the problem of aggregating the criteria that are interdependent, a non-additive function that defines a weight, not only for each criterion but also for each subset of criteria, is needed. Thus, these non-additive functions can model both the importance of criteria and the positive and negative synergies between them. Taking the above into account, we propose the use of the machine criticality index (MCI) λ-fuzzy measure and Choquet fuzzy integral, which can handle both the challenges. According to [52] the Choquet integral has good properties for aggregation. It is continuous, non-decreasing, comprised between min and max, stable under the same transformations of interval scales in the sense of the theory of measurement, and it coincides with a weighted arithmetic mean when the fuzzy measure is additive. In view of the characteristics of the Choquet integral, it has been widely applied to multiple attribute decision-making in many areas [7, 9, 22, 23, 35, 56, 78]. However, the interest in the fuzzy integral is mainly due to its ability to represent interactions between criteria . This is due to the fact that weights in a fuzzy measure are assigned to every subset of all criteria.

3.2. Definitions and notations

The fuzzy set theory has been applied to many problems in different fields of science and engineering. In order to describe this theory, some definitions are presented as follows:

Let $X = \{x_1, \ldots, x_n\}$ be the set of all criteria and $\mathcal{P}(X)$ the power set of X.

Definition 1 (Fuzzy measure, [10])**:** A discrete fuzzy measure on X is a set function μ: $\mathcal{P}(X) \rightarrow [0, 1]$ satisfying the following conditions:

1. $\mu(\emptyset)=0$, $\mu(X)=1$ (boundary condition)
2. if $A \subseteq B \subseteq X$ then $\mu(A) \le \mu(B)$ (monotonic condition).

In this context, μ(A) represents the degree of importance of a given criteria set A. This way, additionally to the weight of a single criterion, the weight of an arbitrary criteria combination is also directly described. The fuzzy measure is additive when if $A \cap B = \emptyset$ then $\mu(A \cup B) = \mu(A) + \mu(B)$ and superadditive (subsdditive) when $\mu(A \cup B) > \mu(A) + \mu(B)$ (respectively $\mu(A \cup B) < \mu(A) + \mu(B)$).

Definition 2 (Discrete Sugeno λ-measure)**:** A discrete fuzzy measure is called Sugeno λ-measure if it satisfies:

3. If $A \cap B = \emptyset$, then $\mu_\lambda(A \cup B) = \mu_\lambda(A) + \mu_\lambda(B) + \lambda\mu_\lambda(A)\mu_\lambda(B)$.

Note that (1) and (2) are fundamental properties for any types of a fuzzy measure and (3) is an additional property of λ-measure. To differentiate this measure from other fuzzy measures, λ-fuzzy measure is denoted by μ_λ. Sugeno [77] proved that given those 3 axioms, a fuzzy measure can be uniquely determined using only n = |X| coefficients μ_i that are often called fuzzy densities which represent the degree of importance of the criteria *i-th* and can be calculated with parametric or nonparametric methods. The λ-measure can be calculated using the following formula:

$$\mu_\lambda(\{x_1, x_2, \ldots, x_n\}) = \left| \sum_{i=1}^{n} \mu_i + \lambda \sum_{i_1=1}^{n-1} \sum_{i_2=i_1+1}^{n} \mu_{i_1}\mu_{i_2} + \lambda^{n-1}\mu_1\mu_2 \cdots \mu_n \right| = \frac{1}{\lambda}\left| \prod_{i=1}^{n}(1+\lambda\mu_i) - 1 \right|$$

Based on the boundary condition in Eq. (1), $\mu_\lambda(X)=1$, λ can be uniquely determined via the following equation:

$$\lambda + 1 = \prod_{i=1}^{n}(\lambda\mu_i + 1), \tag{2}$$

where $\mu_i = \mu(\{x_i\})$, i =1, 2, …, n is known as the fuzzy density function of a single element (singleton), $x_i \in X$.

According to Gürbüz et al. [30] and Hu and Chen [32]:

- If λ < 0 then it implies that the attributes share a redundancy effect. This means a significant increase in the performance of the target can be achieved by only enhancing some attributes in X which have higher individual importance.
- If λ > 0 then it interprets that the attributes share a synergy support effect. This means a significant increase in the performance of the target only can be achieved by simultaneously enhancing all the attributes in X, regardless of their individual importance.
- If λ = 0, then it indicates that the attributes are non-interactive.

Definition 3 (Discrete Choquet integral)**:** Let μ be a discrete fuzzy measure on X. The discrete Choquet integral of function $f: X \rightarrow [0,1]$ with respect to the fuzzy measure μ is defined by:

$$C_\mu(f_1, f_2, \ldots, f_n) = \sum_{i=1}^{n}(f_{(i)} - f_{(i-1)})\mu(A_{(i)}), \tag{3}$$

where: $f_{(i)}$ indicates that the indices have been permutated so that $0 \le f_{(1)} \le \ldots \le f_{(n)} \le 1$, $A_{(i)} = \{x_{(i)}, \ldots, x_{(n)}\}$ and $f_i = f(x_i)$.

Definition 4 (Shapley value - ν_i, [59]: Let μ be a fuzzy measure on X. The Shapley value (or the importance index) for every element $x_i \in X$ is defined by the following formula:

$$\nu_i = \sum_{A \subset X \setminus \{x_i\}}^{n} \gamma_X \left[\mu\left(A \cup \{x_i\}\right) - \mu(A) \right], \tag{4}$$

where:

$$\gamma_X(A) = \frac{(|X| - |A| - 1)!\,|A|!}{|X|!} \tag{5}$$

The Shapley value with respect to the measure μ is a vector $\nu = [\nu_1, \nu_2, \ldots, \nu_n]$. It describes the global importance of every element by considering the effects of all subsets with and without the given element. According to the definition, the Shapley value has the property that the sum of all its components is 1, which can be formulated as $\sum_{i=1}^{n} \nu_i = 1$. Scaled by the factor *n*, the Shapley values greater than 1 indicate that the given element (criterion) is more important than the average.

The Shapley value ranges between 0 and 1. In essence, it measures how much a criterion contributes, on average, to all the coalitions of criteria.

Definition 5 (Interaction Index - $I_{i,j}$, [58]). Let μ be a fuzzy measure on X. The interaction index of the criteria x_i and x_j is defined by:

$$I_{i,j} = \sum_{K \subset X \setminus \{x_i, x_j\}} \frac{(|X| - |K| - 2)!\,|K|!}{(|X| - 1)!} \left[\mu\left(K \cup \{x_i, x_j\}\right) - \mu\left(K \cup \{x_i\}\right) - \mu\left(K \cup \{x_j\}\right) + \mu(K) \right] \tag{6}$$

The interaction index takes values from [-1, 1] interval, where negative (positive) values indicate a negative (positive, synergic) interaction.

Definition 6 (Ordered Weighted Mean - *OWA*, [88]). An OWA aggregation operator is a mapping *OWA*: $[0.1]^n \to [0.\ 1]$ such as:

$$OWA(x_1, \ldots, x_n) = \sum_{i=1}^{n} w_i x_{(i)}, \tag{7}$$

where the weights $w_i \in [0,1]$ for $i = 1, \ldots, n, \sum_{i=1}^{n} w_i = 1$ and $x_{(i)}$ indicates that the indices have been permuted so that $0 \le x_{(1)} \le \ldots \le x_{(n)} \le 1$.

3.3.3. Integrated assessment process for machine criticality identification

The operation process of the Choquet integral for the machine criticality criteria aggregation is described as follows (Figure 5).

The first step in developing a machine criticality index focuses on weighting the individual elements (criteria and sub-criteria). The assessment of the importance of criteria is usually a subjective assessment and is carried out by experts. The subjective approach requires evaluator(s) to evaluate the criteria in terms of a relative importance or influence of the criteria towards the final score [49]. Since this step is carried out by a team of experts and because of their subjectivity and cognitive differences, linguistic variables are used and then they are aggregated by fuzzy arithmetic.

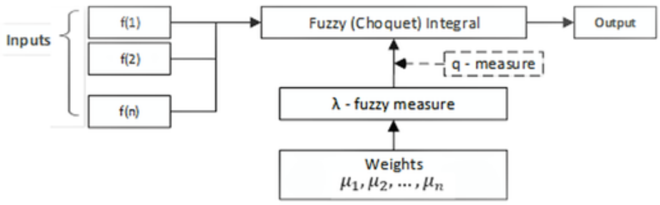

Fig. 5. λ-fuzzy measure and fuzzy integral

The Fuzzy Number Ordered Weighted Average (FN-OWA) operator was used in the model for averaging expert evaluations. According to Sadiq and Tesfamariam [71]) the FN-OWA operator:

- provides a flexible aggregation ranging between the minimum and the maximum operators for fuzzy (or qualitative) data;
- has ability to aggregate not only the quantitative data but can also handle linguistic as well as crisp data;
- can handle the missing information efficiently, i.e., a case of complete ignorance about the value of a given input parameter;
- provides flexibility in handling *exaggeration* and *eclipsing* in the aggregation process;
- the aggregated value obtained through FN-OWA operator retains the same linguistic state as if all input criteria have equal values, i.e., idempotency property of the FN-OWA operator.

Aggregated fuzzy weights are then defuzzied in order to be applied in constructing a fuzzy measure. Mathematically, defuzzifying a fuzzy set is the process of rounding it off from its location to the nearest vertex, what reduces the set into the most typical or representative value. Compared with a fuzzy value, a crisp value is more intuitive and easier for the final comparison because fuzzy sets have partial ordering. These crisp values (fuzzy density) can be treated as an average assessment of the importance of individual criteria/sub-criteria.

The next step is to build a fuzzy measure λ. The fuzzy measure is an extension of a probability measure. Probability measures are usually resistant in representing human subjectivity because of their additivity. In contrast, fuzzy measures do not require this property and, thus, can be interpreted as the subjective measures of a person evaluating an object [81]. This kind of measure is more flexible than a probability. According to Beliakov et al. [3]: Fuzzy measures map each subset of a given set to a weight or importance, what allows for the modelling of complementary or redundant relationships between variables.

There are three kinds of interactions between the assessment criteria: synergy, inhibitory and non-interaction. The fuzzy measure can be applied to all three situations. In order to lower the number of coefficients (which increases exponentially with a number of criteria) and satisfy the monotonicity and continuity, the criticality machine assessment model uses λ-measure (see chapter …, Definition 2).

Let any subset $A_i = \{x_1, x_2, \ldots, x_i\}$ of X and given λ value (as calculated in Eq. (2)), the fuzzy measure $\mu_\lambda(A_n)$, for $1 \le i \le n$ can be determined recursively as:

$$\mu_\lambda(A_1) = \mu_\lambda(\{x_1\}) = \mu_1 \tag{8}$$

$$\mu_\lambda(A_i) = \mu_i + \mu_\lambda(A_{i-1}) + \lambda \mu_i \mu_\lambda(A_{i-1}) \tag{9}$$

In this application, the values of the fuzzy densities of the λ-measure are provided by experts according to their opinion on the worth of information sources. If experts choose to provide values that add to 1, the unique real value of the parameter λ will be zero, and, hence, the λ-measure will actually be a probability-measure even though this might not be the best measure for modeling the system.

One of the problems which can appear in case of expert assessments is the situation in which individual criteria will be rated so high (close to 1) that pairs, triples etc. of the criteria, due to the monotonicity of the fuzzy measure, will have very similar values (effectively equal to 1). While in case of aggregation using a weighted average such a situation is not a problem, in case of a fuzzy measure and the Choquet integral it can lead to undesirable results (shallowing / equalization of the criteria weights and total omission of interactions among criteria).

In order to reduce significantly the impact of these problems on the aggregation result, the q-measure proposed by Mohamed and Xiao [55] was applied. It is an extension of the Sugeno λ-measure that allows to automatically rescale the input density values μi. In practice, using a raw expert input is not a plausible strategy, because the values provided by experts, or obtained by using some computations, are at best on an interval scale with an arbitrary position of one. Therefore, scaling of these numbers is arbitrary, and computing from these numbers is then meaningless. The proposed definition for the q-measure, which is merely a normalization of λ -measure, solves this critical problem efficiently. The q-measure formulation decorrelates λ and the density. Moreover, such a formulation ensures that the q-measure complies with the principle that the fuzzy measure of any set, including the singleton sets, should not be determined by simply considering only that one set, regardless of the whole universe. This is a critical issue especially when we intend to find an appropriate fuzzy measure in order to model a complex system that manifests a high degree of interdependencies among its information sources.

Let $X=\{x_1,x_2,\ldots,x_n\}$ be a finite set. For all sets A, B ⊂ X with $A\cap B=\varnothing$, we define $\mu:2^X\to[0,1]$ by:

$$\mu(X)=1$$
$$\mu(A\cup B)=\mu(A)+\mu(B)+\lambda\mu(A)\mu(B) \tag{10}$$

for any choice of $\lambda\geq -1$. The only two constraints on the choice of a density generator value are:

$$0\leq\mu_i\leq 1, i=1,2,\ldots,n \tag{11}$$

$$\sum_{i=1}^{n}\mu_i>0 \tag{12}$$

enforcing the density generators to have values in the unit interval with at least one of the values being strictly positive in order to insure a proper definition of the proposed fuzzy measure. Given a set of the density generator values $\{\mu_1,\mu_2,\ldots,\mu_n\}$ that satisfy the requirements (11) and (12) Mohamed and Xiao [55] defined the q-measure μ_q: $2^X\to[0,1]$:

$$\mu_q(A)=\frac{\mu(A)}{\mu(X)}\forall A \tag{13}$$

It is called the q-measure because it is defined with the aforementioned quotient. Using Eq. (13), for any choice of the variable $\lambda\in[-1,\infty)$, Mohamed and Xiao [55] construct a fuzzy measure. This provides a definition for a class of various fuzzy measures specified by the choice of the variable. The Sugeno λ-measure is a special case in this class, when λ is selected such that μ(X) = 1. All fuzzy measures in this research are obtained by the application of this procedure to expert data.

It is important to note that in a fuzzy measure the importance of a single criterion or a pair of criteria is not solely determined by $\mu(\{x_i\})$ or $\mu(\{x_i,x_j\})$. One needs to consider all $\mu(A)$ such as $x_i\in A$ or $\{x_i,x_j\}\subseteq A$. Murofushi [59] and Murofushi and Soneda [58] proposed a solution to this problem based on the game theory for a single criterion and utility theory for pairs of criteria. Based on a fuzzy measure, the importance index (Shapley value) and interaction indices of different perspectives and criteria were defined.

When a fuzzy measure is constructed, the next step is to apply it in the Choquet integral to obtain the value of MCI. The Choquet integral (Definition 3) with respect to a fuzzy measure, compute an average of their inputs while also accounting for input interactions. This way, redundant inputs are not double counted while complementary inputs reinforce each other. Thanks to the stability of Choquet integral under positive linear transformations, the exact numerical scale in relation to which the calculations are made is not relevant. As such, the collection of the data from experts is a simplified way and allows for the assessment with the use of a linguistic scale.

4. Machine criticality assessment model for aviation industry – results of empirical studies

4.1. Development of the machine criticality assessment model

The research on the validity of the criteria for assessing the criticality of machines was carried out in the aviation industry. Based on the analysis of the research results (chapter 3.2), thirteen criteria were selected. They were considered important in this industry (the highest total value for the criteria and the greatest consistency of respondents' answers - standard deviation). These criteria are: "Machine replacement in case of a failure"; "Degree of influence on other tasks in case of a machine failure"; "Costs incurred by production for machine downtime (breakdown)"; "Number of nonconformities due to a machine failure during the year"; "Degree of machine influence on the final product quality"; "Costs of non-conforming products as the result of a failure"; "Frequency of failures per year"; "Average downtime of a technical facility due to failures and repairs"; "Spare parts availability"; "Failure elimination costs (excluding OHS and environmental costs)"; "In case of a failure, the degree of influence on the working environment"; "In case of a failure, the degree of risk to the environment"; "Machine failure costs due to health, safety and the environment".

A large number of criteria indicated by experts shows that the problem of a machine criticality assessment on a manufacturing system level is a complex multi-dimensional decision problem [79]In order to solve this problem, an enterprise has to consider different viewpoints from various stakeholders and, thus, include many (not always compatible) goals in a decision-making process. A possible strategy to deal with this problem is to combine multiple goals simultaneously into a hierarchical structure mapping the main stakeholder groups and the issues relevant to each of them. Considering the above, the problem of assessing machine criticality was structured as a hierarchy that shows the criteria and sub-criteria. This type of presentation is enterprise-friendly and enables more effective analysis.

The thirteen criteria are grouped into four categories: 1) Production - P, 2) Quality - Q, 3) Maintenance - M, and 4) Safety, Health and the Environment - SHE. The adopted categories of grouping (hereinafter referred to as criteria) reflect the main groups of stakeholders, i.e. those who are affected by the criticality of machines and which influence this criticality. The model was discussed with experts from the aviation industry and its final structure is shown in Figure 6.

Because of the formulated goal, the research was of qualitative nature. Qualitative research does not aim to draw a statistical inference or produce a statistically representative sample. Therefore, purposive sampling (also called judgment sampling) was used to select quality informants for this study by Tongco [83]. He asserted that there is no cap on how many informants should be considered in purposive sampling, but five is the minimum number for data to be reliable. According to Gray [24] and Guest et al. [25] a sample size of between six and twelve interviews is often sufficient to achieve data saturation for every theme. Experts from 8 aviation manufacturing companies were invited to participate in the research.

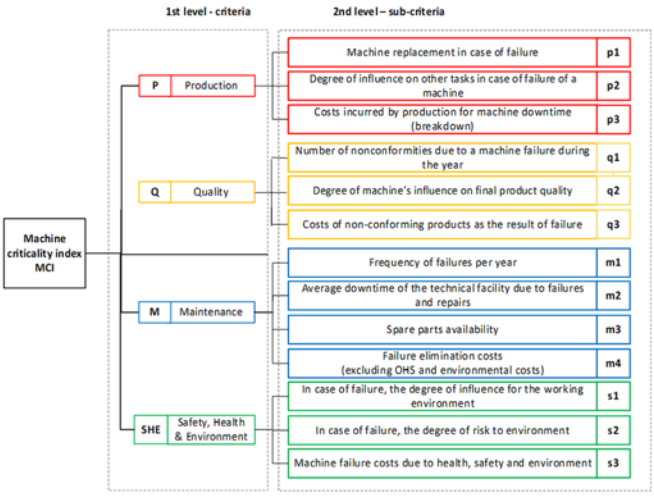

Fig. 6. Machine criticality assessment criteria and related sub-criteria

4.2. Determining the degree of importance of the machine criticality criteria and sub-criteria

The determination of the importance of criteria was carried out by experts according to the scheme (Figure 6):

(1) assessment of the importance of the criteria and sub-criteria by experts;
(2) calculating the an average value for the criteria and sub-criteria;
(3) developing a λ measure;
(4) determining the importance and interactions between the criteria and sub-criteria.

First, the experts evaluated the importance of the criteria/sub-criteria in a questionnaire. To increase the accuracy of the machine criticality assessment, all aerospace experts in our sample checked that the machine criticality frame used was working in their maintenance systems before conducting the assessment. The experts were asked to answer the following questions: How important is the X criterion / sub-criterion if it were to be used alone to assess the machine criticality? (following the hierarchical model - Figure 6, with the five-level linguistic scale (Table 3)). The experts had no imposed numerical interpretation of the linguistic variables used [91].

Table 3. Linguistic values of the criteria/sub-criteria importance grade

Linguistic terms	Description	Linguistic values
Very important	the criterion/sub-criterion can be used alone to assess the entire level	(0.75, 1.0, 1.0)
Important		(0.5, 0.75, 1.0)
Moderately important		(0.25, 0.5, 0.75)
Equal important		(0, 0.25, 0.5)
Irrelevant	the criterion/sub-criterion is almost irrelevant to the level assessment	(0, 0, 0.25)

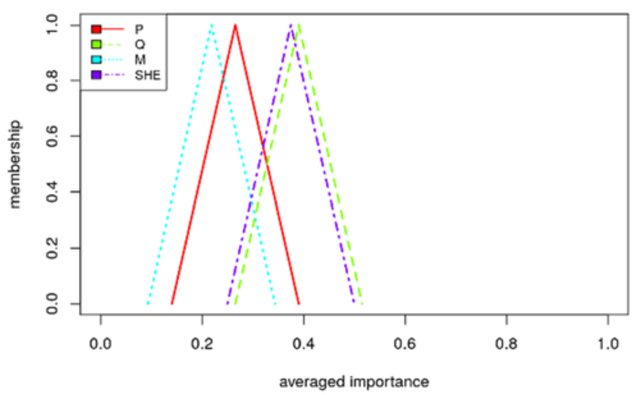

Fig. 7. Averaged importance values for the first level criteria

The average importance for each sub-criterion was calculated using FN-OWA. As a result of this aggregation method, the most extreme evaluations were rejected. The same method was used to aggregate expert assessments for the criteria (second level). Averaged importance values for the first level criteria are given in Figure 7.

Table 4. Fuzzy densities μi, fuzzy measure and Shapley value (ν_i) for sub-criteria

Criteria	Sub-criteria	$\mu_i(\bullet)$	λ	ν_i
Production	p1	0.3750	-0.0458	1.1085
	p2	0.3281		0.9690
	p3	0.3125		0.9225
Quality	q1	0.3125	0.1526	0.9840
	q2	0.3438		1.0800
	q3	0.2969		0.9360
Maintenance	m1	0.2250	0.1068	0.9360
	m2	0.2875		1.1920
	m3	0.2500		1.0388
	m4	0.2000		0.8332
SHE	s1	0.3594	0.0484	1.0944
	s2	0.3438		1.0473
	s3	0.2813		0.8583

The last step was to calculate single numerical values for each of the fuzzy numbers. These values (fuzzy densities μ_i) can be treated as an average assessment of the importance of individual criterion/sub-criterion. Using Center of Gravity defuzzyfication method led to the results presented in Table 4 and 5.

The calculated values of μ_i were used to develop a fuzzy measure. An algorithm presented in Mohamed and Xiao [55] was implemented in the R 3.4.4 Statistical Computing Platform and applied without fixing λ to the averaged importance values in order to construct the Sugeno λ-measure (Definition 2). Once the fuzzy measures for the sub-criteria and criteria are identified, the next step is to compute the Shapley value using Eq 4 and Eq 5. The obtained fuzzy densities μ_i, λ-values for the sub-criteria and criteria as well as the scaled Shapley value are presented in Table 3 and Table 4.

Table 5. Fuzzy densities μi, fuzzy measure and Shapley value (ν_i) for criteria

Criteria	$\mu_i(\bullet)$	λ	ν_i
Production	0.2656	-0.4788	0.8368
Quality	0.3906		1.2688
Maintenance	0.2188		0.6816
SHE	0.3750		1.2132

In Table 5, the λ value equals -0.4788212, what indicates a high degree of an interaction between various criteria for assessing the machine criticality. Based on the fuzzy measure (Table 4 and Table 5), the importance index (Shapley value) of different criteria and sub-criteria was defined.

The Shapley value measures a relative importance of each sub-criterion/criterion in terms of its contribution to the score of each coalition [7]. It can measure the importance of each feature in the contribution to the machine criticality assessing problem better. The results presented in Table 5 indicate that the most important criteria are 'Quality' (ν_i=1.2688) and "Safety, Health and the Environment" (ν_i=1.2132), whereas the 'Maintenance' criterion is the least important (ν_i=0.6816). The results presented in Table 3 apply to the value of the Shapley index for the sub-criteria describing a particular criterion. Analyzing the criterion 'Production" (P), the experts indicate that "Machine replacement in case of a failure - p1" is more important than "Degree of influence on other tasks in case of a machine failure - p2" and "Costs incurred by production for machine downtime (breakdown) - p3". Assessing the criterion "Quality" (Q) (Table 3), the experts indicate that the sub-criteria "Degree of machine's influence on a final product quality - q2" is the most important. Another criterion analyzed is "Maintenance" (M). The distribution of the importance of the assessment sub-criteria indicates that the most important are "Average downtime of a technical facility due to failures and repairs - m2" and "Spare parts availability - m3". The fourth criterion is 'Innovation and development' (ID). According to the experts' assessment the most important criteria are "In case of a failure, the degree of influence on the working environment - s1" and "In case of a failure, the degree of risk to the environment - s2"

Another interesting aspect is that of the interaction among the criteria. When the fuzzy measure is not additive, then some criteria interact. The weight of sets of the sub-criteria taken together is determined by the Interaction Index, measuring the synergies or redundancies existing between the sets of variables. The obtained interaction index for the sub-criteria is presented in Table 6.

Table 6. Interaction Index $I_{i,j}$ for sub-criteria

Criteria					
	P	Sub-criteria	(p1, p2)	(p1, p3)	(p2, p3)
		$I_{i,j}$	-0.0056	-0.0053	-0.0047
	Q	Sub-criteria	(q1, q2)	(q1, q3)	(q2, q3)
		$I_{i,j}$	0.0168	0.0145	0.0159
	M	Sub-criteria	(m1, m2)	(m1, m3)	(m2, m3)
		$I_{i,j}$	0.0071	0.0062	0.0079
		Sub-criteria	(m1, m4)	(m2, m4)	(m3, m4)
		$I_{i,j}$	0.0049	0.0063	0.0055
	SHE	Sub-criteria	(s1, s2)	(s1, s3)	(s2, s3)
		$I_{i,j}$	0.0060	0.0049	0.0047

According to the assessment of the experts from the aviation industry, the sub-criteria describing the criterion "Production" are redundant, which means that some criteria should be rejected. Nevertheless, since the values of the interaction ratios are close to zero, it is difficult to draw binding conclusions. The interaction indexes between the sub-criteria describing the remaining criteria for assessing the criticality of machines are positive. Therefore, it can be assumed that they are synergistic (see chapter 3.3.2). The most complementary criteria are q1 and q2, and q2 and q3.

4.3. Numerical example

The above multicriteria criticality assessment model was applied to assess Machine Criticality Index (MCI) in a medium size aviation factory. The calculation procedure of MCI requires the fuzzy measure (μ) and actual values of the sub-criteria obtained from the company assessment team (f_i) (see an outline of this procedure in Fig. 5). Based on the available data collected in various departments of the company, the supervisor of the maintenance department assessed each of the 13 sub-criteria specified in the model for the selected machine A (Figure 6). To assess the value of the individual sub-criteria a point method was selected. The literature review [66, 75] indicates that this is the most common method of assessing criteria used in the aviation industry. Table 7 presents an assessment matrix for the example criteria.

Table 8 presents the value of the sub-criteria f_i. The aggregated values $C_\mu(f_1, f_2, \ldots, f_n)$ was obtained by Eq.(3) using the importance weighting of $\mu_i(\bullet)$ for the sub-criteria and for criteria (table 3) in R 3.4.4 Statistical Computing Platform. The aggregated value $C_\mu(f_1, f_2, \ldots, f_n)$ in Table 8 represents the overall criticality of the machine A of the four criteria: Production (P); Quality (Q), Maintenance (M) and (SHE). Based on Table 7, the Choquet integral values $C_\mu(f_1, f_2, \ldots, f_n)$ of each sub-criterion can further be employed to determine the next f_i and obtain the MCI for machine A (Table 9).

The output result is easy to interpret and understand, and can thus be used directly by all maintenance stakeholders. The value of $\mu_\lambda(\bullet)$ enables the assessment of the impact of each of the analyzed criteria on the final value of the MCI index for machine A. Among the analyzed criteria, „Quality" has the greatest impact (μ_λ (M, SHE, Q)−μ_λ (M, SHE) = 0.287). Therefore, in order to improve the maintenance strategies planned and implemented for machine A, first of all, actions should be defined in relation to the sub-criteria q1, q2 and q3. In this group of sub-criteria, q1 has the greatest impact (the highest value of ν_i=1.1085), therefore, potential solutions should be targeted at this area of impact.

5. Conclusions

Manufacturing equipment (machines, devices) are essential to production environments. However, due to the importance in the product realization process and the consequences of failure (e.g. environmental impact, human health and safety), not all machines are equally important. Given that each enterprise has limited resources (e.g. financial, human, material), it is necessary to prioritize (machine criticality assessment) and have a strategy to manage machines according to how critical they are to operation and maintenance.

In this paper the problem of machine criticality was analyzed. The criteria and methods proposed for assessing the criticality of machines were identified. Then, the research was conducted to identify the most important criteria used to assess the criticality of machines in various types of industries. On the basis of the obtained results, the criteria and industry, for which the machine criticality assessment model was developed, were selected.

The proposed model of the machine criticality assessment has a two – levelled hierarchical structure. On the first level of the hierarchical structure there are the criticality assessment process stakeholders. The criticality assessment process stakeholders are: maintenance managers who plan and realize maintenance activities and production, as well as quality and SHE managers, on whom the decisions and activities have impact. The second level of the hierarchical structure are sub-criteria – the aspects which are significant for all criticality assessment process stakeholders.

In order to assess the machine criticality the Machine Criticality Index was developed. The aim of the MCI index is to measure outputs of different criticality criteria and sub- criteria, and integrate them in one single index. Weighting and aggregation is an important step in this procedure. There are various weighting and aggregation methods related to specific purposes. Because the criteria and sub- criteria of the machine criticality assessment are independent, in order to aggregate them a non-additive fuzzy integral was selected. The fuzzy integral method applies fuzzy measures to deal with the problems of human subjective perception and uncertainty as well as to address the level of interdependency effects among the criteria [77]. In this research, we are motivated to implement the theory of fuzzy measures to model the

Table 7. The ranking of sub-criteria assessment – example

Ranking scale	Sub-criteria			
	p3	q2	s1	s2
	The failure			
1	has no effect on production losses at all	has no effect on product quality at all	has no effect on safety at all	has no effect on environment at all
2	can cause minor losses of production (p3 < a)	can create defects that will cause rejection or rework of parts of production lots	can cause only small injuries with no absence of the worker	can cause only a small impact only in the delimited area of occurrence inside the department
3	can cause significant losses of production a ≤ p3 < b	can create defects that will block online lots of production, causing high volumes of rejection or rework	can cause injuries with temporary absence of the worker	can cause an environmental impact internally in the plant
4	can cause extensive losses of production p3 ≥ b	can create defects that will be perceived by a customer (cannot be blocked inside the plant)	can cause death or injuries with permanent absence of the worker	can cause an environmental impact outside the limits of the plant

Table 8. The fuzzy measure and aggregated values of P, Q, M and SHE for the machine A

Criteria	Sub-criteria	f_i	$\mu_i(\bullet)$	$C_\mu(f_1, f_2, \ldots, f_n)$ (λ – value)	$\mu_\lambda(\bullet)$
Production	p1	1	0.3750	P = 1.636 λ = -0.0458	μ_λ(p2)=0.328
	p2	2	0.3281		μ_λ(p2, p3)=0.636
	p3	2	0.3125		μ_λ(p2,p3,p1)=1.000
Quality	q1	2	0.3125	Q = 2.000 λ = 0.1526	u_λ(q1)=0.313
	q2	2	0.3438		μ_λ(q1,q2)=0.673
	q3	2	0.2969		μ_λ(q1,q2,q3)=1.000
Maintenance	m1	3	0.2250	M = 2.519 λ = 0.1068	μ_λ(m1)=0.225
	m2	3	0.2875		μ_λ(m1,m2)=0.519
	m3	2	0.2500		μ_λ(m1,m2,m3)=0.783
	m4	2	0.2000		μ_λ(m1,m2,m3,m4)=1.000
SHE	s1	3	0.3594	SHE = 2.068 λ = 0.0484	μ_λ(s1)=0.359
	s2	2	0.3438		μ_λ(s1,s2)=0.709
	s3	1	0.2813		μ_λ(s1,s2,s3)=1.000

Table 9. Fuzzy measure and value of MCI for machine A

Criteria	f_i	$\mu_i(\bullet)$	$C_\mu(f_1, f_2, \ldots, f_n)$ **λ - value**	$\mu_\lambda(\bullet)$
Production	1.636	0.2656	MCI = 2.079 λ = -0.4788	μ_λ(M)=0.219
Quality	2.000	0.3906		μ_λ(M,SHE)=0.554
Maintenance	2.519	0.2188		μ_λ(M,SHE,Q)=0.841
SHE	2.068	0.3750		μ_λ(M,SHE,Q,P)=1.000

importance and interaction between the features in the Choquet integral. According to the best knowledge of the authors, there is a lack of such framework of the criticality machine assessment in the previous research. Based on the fuzzy measure, the importance index (Shapley value) and interaction index of different criteria and sub-criteria were defined. The analysis of Shapley values and interaction indexes demonstrate that the presented fuzzy machine criticality assessment is able to provide maintenance managers with a better understanding of the importance of individual criteria and sub-criteria in the assessment of the machine criticality and their impact on the final value of the MCI index. Taking into account the final value of the MCI index they are able to develop better planning of machine maintenance programmes and resources allocation.

The created model has some limitations. First of all, the model was developed only based on the research conducted in enterprises from the aviation industry. Secondly, in these enterprises only discrete manufacturing processes were realized. Therefore, some of the analzyed criteria cannot be significant for continuous manufacturing processes, e.g. the sub–criterion p1 (Machine replacement in case of a failure). Thirdly, the calculation of the MCI index from a mathematical point of view is complicated. Therefore, it could be a potential limitation of the application of this model in practice. Finally, the development of an intelligent manufacturing system and digital twin technology with rich sensor data and AI technique for diagnostics and prognostics would have a great influence on the calculation of the MCI index. Thus, carrying out relevant research is suggested to be continued.

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